



# Multi Sensor Image Fusion using Empirical Mode Decomposition

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**Abstract:** Image fusion is a process of combining relevant information from two or more images from different sensors based on certain algorithm. Many algorithms have been proposed for pixel level image fusion. In this paper, Empirical Mode Decomposition is the recent, powerful tool for adaptive multi scale analysis of non stationary signals that decomposes them into Intrinsic Mode Functions (IMFs). Hence an attempt is made to use EMD for multi sensor image fusion. Two types of Empirical Mode Decomposition algorithms viz. BEMD (Bi dimensional Empirical Mode Decomposition) and VEMD (Vectorized Empirical Mode Decomposition) are used to decompose the images to get Intrinsic Mode Functions (IMFs). It is concluded that both algorithms are performed similar but VEMD is computationally very simple. Fusion algorithms viz., Simple Averaging (SA), Principal Component Analysis (PCA), Stationary Wavelet Transform (SWT) and Laplacian Pyramid (LP) are applied on each IMFs to generate the fused IMFs. Fused image is reconstructed by summing all the fused IMFs. Objective and subjective fusion quality evaluation metrics are used to evaluate the performance of these fusion algorithms. It is concluded that SWT based image fusion algorithm performs better followed by LP based fusion algorithm. It is also concluded that fusion quality is degraded by using more number of decomposition levels in wavelets and pyramid based image fusion algorithms. From this study, it is concluded that both BEMD and VEMD with SWT based image fusion algorithm provides good fusion results. VEMD with SWT based image fusion algorithm is computationally simple and can be used for real time image fusion applications.

**Keywords:** Image Fusion, Empirical mode decomposition, Performance Metrics.

## I. INTRODUCTION

Empirical Mode Decomposition (EMD) was first introduced by Huang et al. [1] and provides a powerful tool for adaptive multi scale analysis of non stationary signals. It is a non-parametric data-driven analysis tool that decomposes non-linear non-stationary signals into Intrinsic Mode Functions (IMFs). The final representation of signal is an energy-frequency distribution, designated as Huang spectrum [1] that gives sharp identifications of salient information. With the Hilbert transform, the IMFs allow representation of instantaneous frequencies as functions of time. The main conceptual benefits are the decomposition of parent signal into IMFs and the visualization of time-frequency characteristics.

### A. BEMD

EMD has many interesting features and an important feature is, it is fully adaptive multi scale decomposition. This is because EMD operates on the local extremum sequence and the decomposition is carried out by direct extraction of the local energy associated with the intrinsic time-scales of the signal itself. This is different from the wavelet-based multi scale analysis that characterizes the scale of a signal event using pre-specified basis functions. Owing to this feature, EMD is highly promising in dealing with other problems of a multi scale nature. EMD found various advantages and it can be useful for two dimensional data analysis [1] [2].

An image is a bi dimensional IMF if it has a zero mean, if the maxima are positive and the minima are negative and if the number of maxima equals the number of minima. Bi dimensional empirical mode decomposition (BEMD) method is a relatively new, but potential image processing algorithm. BEMD decomposes an image into multiple hierarchical components known as bi dimensional intrinsic mode functions (BIMFs) and a bi dimensional residue, based on the local spatial variations or scales of the image.

In BEMD using Finite Element method, the local mean surface of a two-dimensional dataset is generated directly from the characteristic data points rather than from the upper and lower envelopes. This overcomes the problem of



possible over shootings between the upper and lower envelopes. Our method avoids constructing two different two dimensional interpolating surfaces (the upper and lower envelopes), which is normally a difficult task and requires much computational cost. In addition, the characteristic data points in our method include not only the local maxima and minima, but also the saddle points, which are a distinct feature of two-dimensional data. In this paper, finite element method is used for fusing the images using EMD [3].

### **B. VEMD**

Bi dimensional Empirical Mode decomposition (BEMD) is computationally complex and involves a series of steps. As it is two dimensional, every row and column have to be processed separately. This in turn will increase the computation of algorithm and on the other hand it is time consuming. BEMD by finite element method is not mathematically strong which further adds its disadvantage. Interpolation error will also be present and triangle mesh formation using Delaunay method will also introduce its own error, which in turn paved a way for a faster, computationally inexpensive algorithm called Vectorized Empirical Mode decomposition (VEMD) [4]. The algorithm of VEMD is simple and is explained as below. Converting a two dimensional data to one dimension and then employing the one-dimensional EMD could be an efficient approach to deal with some image processing problems. This process would be fastest as expected than the other EMD methods. An image is vectorized and one dimensional EMD is applied to two vectors and this process is called VEMD. The image  $I(x,y)$  of size  $M \times N$  is divided into rows and concatenates these rows to form a 1D vector data  $I(x)$  whose size would be  $MN$ . 1D EMD is the applied on the resultant vectorized data. The resultant fused signal is converted back into the image by reversing the procedure.

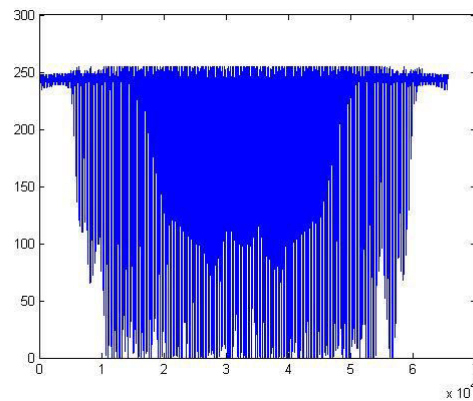
## **II. IMAGE FUSION**

Various image fusion algorithms are in literature and an attempt has been made to fuse the images using empirical mode decomposition. The images to be fused are decomposed to several IMFs using the above BEMD process. Fusion is performed at the decomposition level and the fused IMFs are reconstructed to realize the fused image. The decomposed IMFs of the images are fused using four methods viz. Simple Averaging, Principle Component Analysis, Discrete Wavelet Transform and Laplacian pyramid [5][6][7]. An important point to note in image fusion using EMD is that the number of IMFs should be fixed. The number of IMFs can be different for two images and fusion of IMFs is not possible. Hence the number of IMFs should be fixed in the fusion process. One of the important prerequisites to apply fusion techniques to source images is the image registration, i.e., the information in the source images is needed to be adequately aligned and registered prior to fusion of the images. In this thesis, it is assumed that the source images are already registered.

## **III. RESULTS AND DISCUSSION**

Reference image along with images to be fused are used to compare the fusion performance of BEMD and VEMD based fusion algorithms. First image set contains out of focus images and the second image set contains multi spectral images. First section explains about the image fusion of multi focus images followed by the image fusion of multi spectral images.

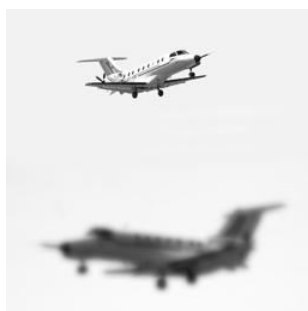
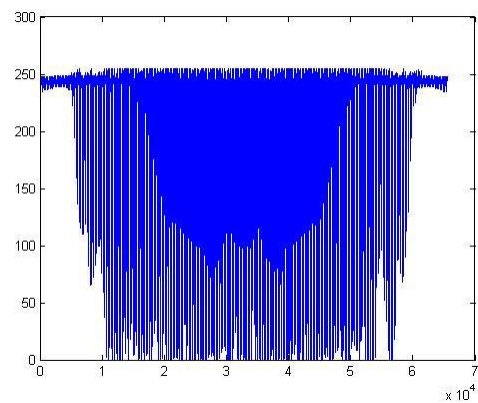
The results for fusion of multi focus images using VEMD and BEMD are discussed here. The National Aerospace Laboratories indigenous aircraft SARAS, shown in Fig. 1a is considered as a reference image (left half: true image and right half: represented in vector form) to evaluate the performance of the fusion algorithms. The complementary pair input images and are taken to evaluate the fusion algorithm and these images are shown in Fig. 1b. The complementary pair has been created by blurring the reference image with a Gaussian mask at the top and bottom half respectively. The IMFs of each image after applying VEMD and BEMD are shown in the Figure 2a – 2d (1<sup>st</sup> column: with BEMD & 1<sup>nd</sup> column: VEMD).



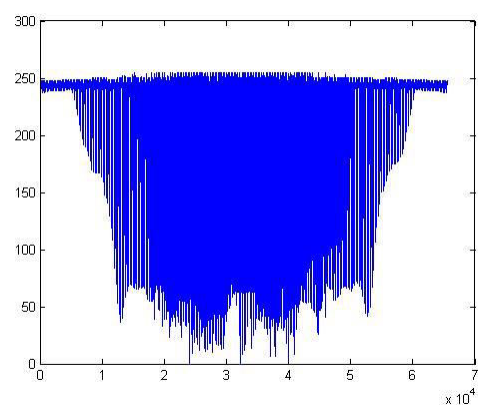
**Figure 1a True image (ground truth)**



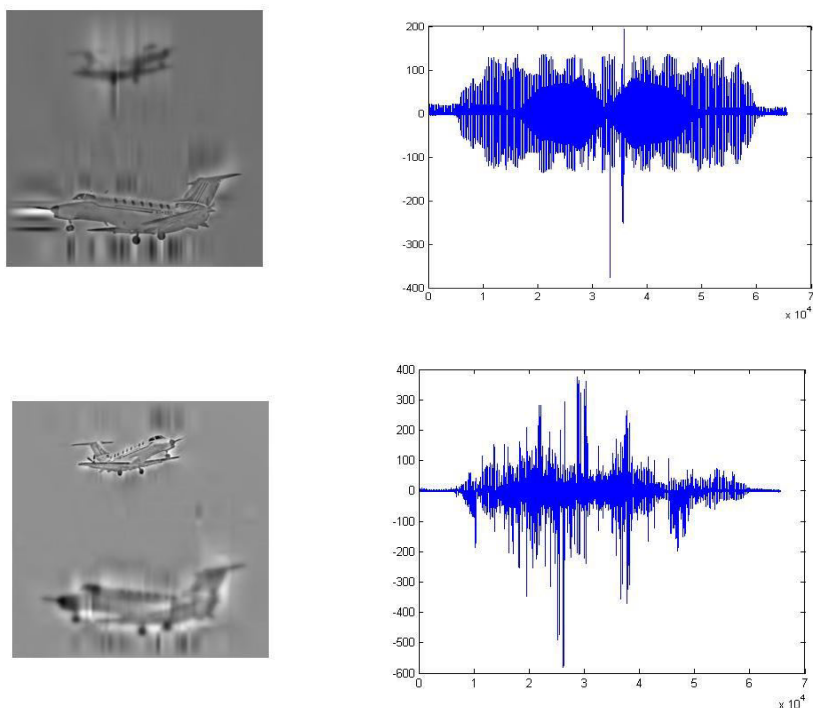
**Image 1**



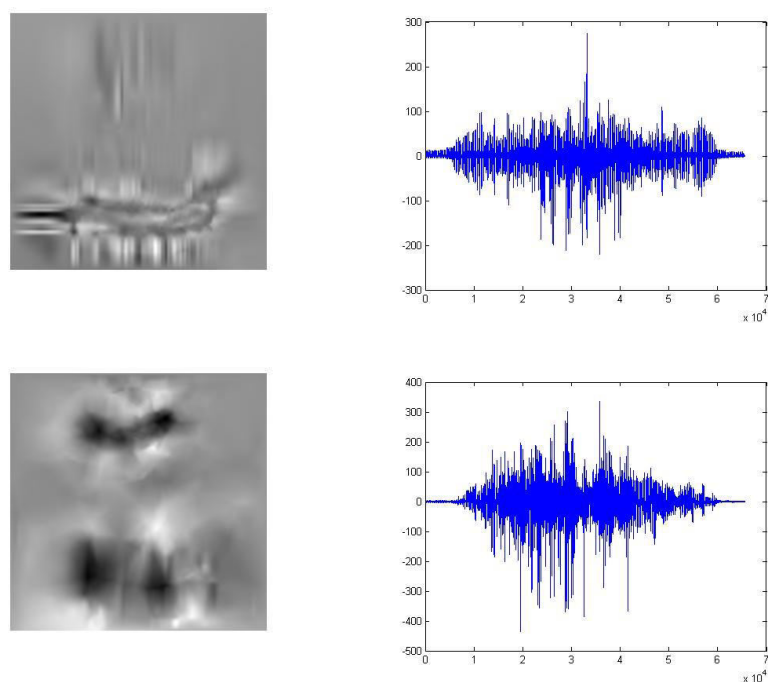
**Image 2**



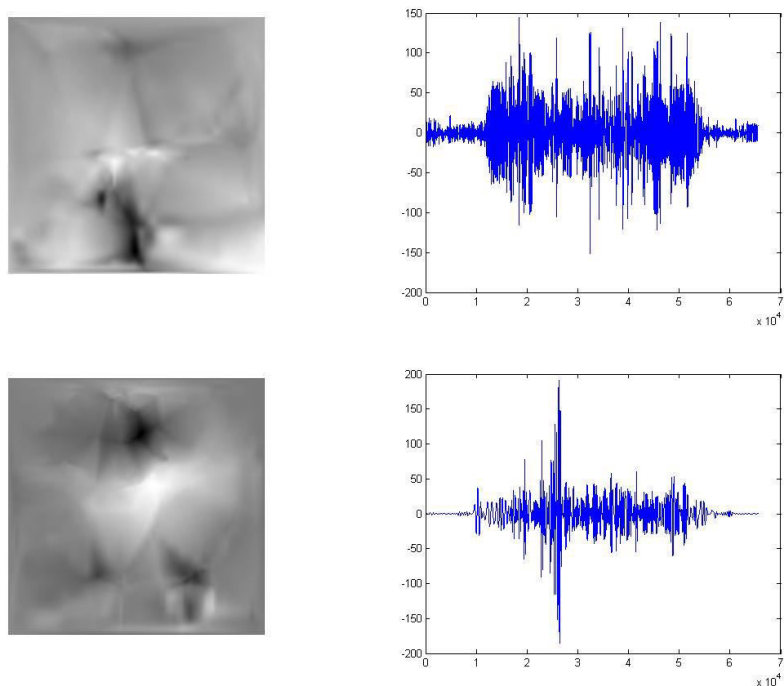
**Fig-1b Images to be fused**



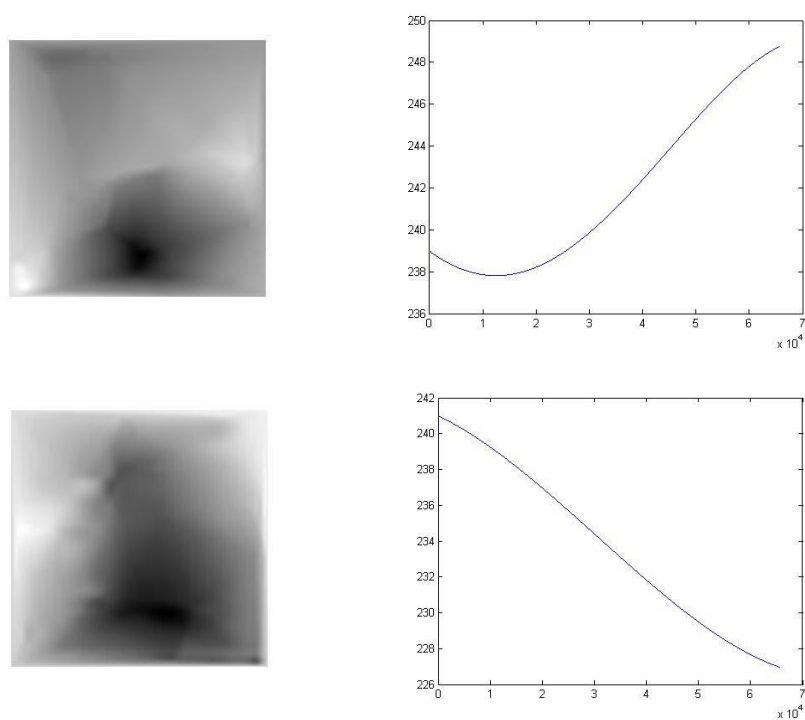
**Fig-2a. First IMF (top row: BMED and VEMD for image 1 and second row: BMED and VEMD for image 2)**



**Fig-2b Second IMF (top row: BMED and VEMD for image 1 and second row: BMED and VEMD for image 2)**

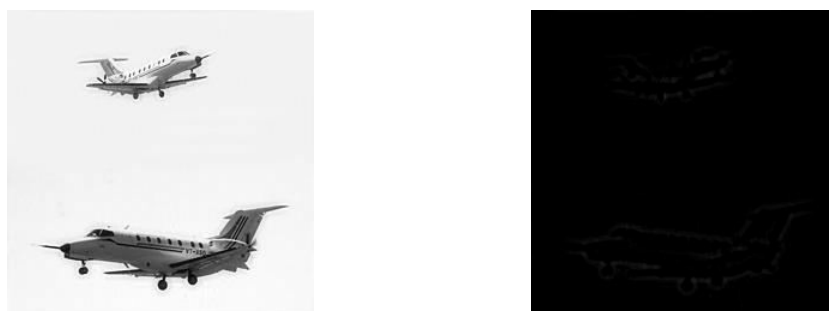


**Fig-2c Fifth IMF (top row: BMED and VEMD for image 1 and second row: BMED and VEMD for image 2)**



**Fig-2d Residua, the last IMF (top row: BMED and VEMD for image 1 and second row: BMED and VEMD for image 2)**

The IMFs of each images obtained using VEMD and BEMD are fused using four methods viz. Simple averaging (SA), Principle Component Analysis (PCA), Stationary Wavelet Transform (SWT) and Laplacian Pyramid (LP). The fused image and error image using BEMD with SWT is shown in Fig-3a and similarly, fused image and error image using VEMD with SWT is shown in Fig-3b. All the fused images look similar from visual point of view.



**Fig-3a. Fused and error image using SWT based image fusion algorithm - BEMD**



**Fig-3b. Fused and error image using SWT based image fusion algorithm – VEMD**

The fused image and error image using BEMD with LP is shown in Fig-4a and similarly, fused image and error image using VEMD with LP is shown in Fig-4b. From Fig-3 and Fig-4, it is observed that SWT based image provides better fusion results.



**Fig-4a. Fused and error image using LP based image fusion algorithm- BEMD**



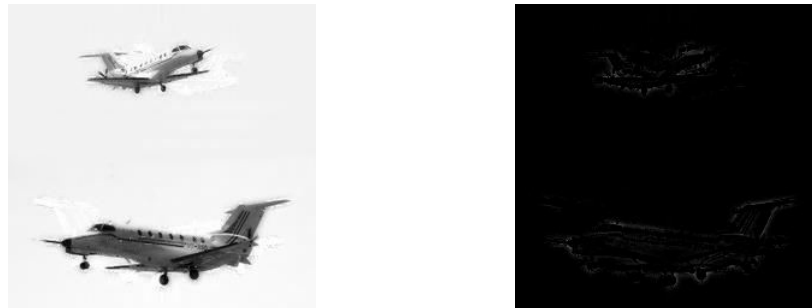


Fig-4b. Fused and error image using LP based image fusion algorithm- VEMD

Most commonly used performance metric for objective evaluation are Root Mean Square Error (RMSE), Peak Signal to Noise Ratio (PSNR), standard deviation (SD), spectral angle mapper (SAM), correlation coefficient (CC), maximum difference (MD), visual information fidelity of fusion (VIFF) and execution time etc.. Various other performance metrics are available for the objective evaluation of image fusion quality [5][8][9][10]. Fusion quality evaluation metrics for both BEMD and VEMD algorithms are shown in Table 1. It is observed that RMSE is smaller when compared with the pixel level image fusion presented in Ref. [5]. It shows that the present algorithm had performed well. Table 2 shows the RMSE values for increasing number of IMFs with the increase number of wavelet decomposition levels in fusion process. It is observed from the table that three levels of wavelet decompositions gave less RMSE values for both BEMD and VEMD algorithm. The error value is less if IMF=2 and the value increases for the increasing number of IMFs for BEMD algorithm. In case of VEMD, the error value is less for IMF=1 and the error increases with the increasing IMF number. VEMD decomposes image up to 11 IMFs and BEMD decomposes the image up to 24 IMFs. Hence for VEMD, we cannot increase the IMFs beyond 11. Table 3 shows the RMSE values for increasing the number of IMFs with the increasing the number of LP decomposition levels in fusion process. It is observed from the table that 2 levels of pyramid decompositions gave less RMSE values for both BEMD and VEMD algorithm. The error value is less if IMF=2 and the value increases for the increasing number of IMFs for BEMD and VEMD algorithm. In this case also, BEMD performs better than VEMD with the expense of computational complexity.

Table 1 Performance metrics for the evaluation of image fusion

Fusion Algorithm		Metric							
		RMSE	SD	PSNR	SAM	CC	MD	VIFF	Time
SA	BEMD	8.417	45.656	38.914	0.036	0.9993	70.500	0.8121	99.062
	VEMD	8.417	45.656	38.914	0.036	0.9993	70.500	0.8121	7.664
PCA	BEMD	8.393	45.667	38.926	0.036	0.9993	69.864	0.8128	84.948
	VEMD	8.398	45.667	38.923	0.036	0.9993	69.998	0.8127	7.606
SWT	BEMD	<b>2.550</b>	48.805	<b>44.099</b>	<b>0.012</b>	<b>0.9999</b>	<b>30.921</b>	<b>0.9510</b>	84.580
	VEMD	3.786	<b>48.890</b>	42.285	0.016	<b>0.9999</b>	50.129	0.9330	<b>7.426</b>
LP	BEMD	4.72	47.680	41.426	0.020	0.9998	53.465	0.9013	93.391
	VEMD	5.20	47.201	41.006	0.022	0.9998	41.832	0.8888	40.390



Table 2a RMSE values for increasing number of IMFs with the increase of decomposition levels in SWT (BEMD)

No. of IMFs	No. of decomposition levels							
	1	2	3	4	5	8	10	15
1	6.858	5.139	5.577	7.475	9.871	11.182	NA	NA
2	6.809	4.381	<b>2.550</b>	7.438	11.290	13.987	NA	NA
3	6.822	4.419	2.831	7.866	14.132	19.589	NA	NA
4	6.875	4.613	2.923	7.916	14.017	21.282	NA	NA
5	6.828	4.451	2.963	7.913	14.357	22.493	NA	NA
8	6.925	4.806	3.080	8.302	14.271	22.489	NA	NA
10	6.893	3.550	3.036	8.071	13.960	23.268	NA	NA
15	6.830	4.455	2.960	7.905	14.281	25.798	NA	NA

Table 2b RMSE values for increasing number of IMFs with the increase of decomposition levels in SWT (VEMD)

No. of IMFs	No. of decomposition levels							
	1	2	3	4	5	8	10	15
1	7.162	5.102	<b>3.793</b>	6.588	8.562	13.473	NA	NA
2	7.162	5.095	3.873	7.772	14.456	24.579	NA	NA
4	7.162	5.095	3.872	7.845	15.161	34.952	NA	NA
5	7.162	5.095	3.872	7.845	15.155	34.975	NA	NA
8	7.162	5.095	3.872	7.845	15.155	34.974	NA	NA
10	7.162	5.095	3.872	7.845	15.155	34.974	NA	NA
15	NA	NA	NA	NA	NA	NA	NA	NA

Table 3a RMSE values for increasing number of IMFs with the increase of decomposition levels in LP (BEMD)

IMFs	No. of decomposition levels							
	1	2	3	4	5	8	10	15
1	8.417	<b>4.460</b>	4.973	10.326	15.171	16.753	16.726	16.726
2	8.417	4.652	5.849	11.839	18.757	22.103	22.139	22.139
3	8.417	4.689	6.114	12.474	19.937	23.781	23.972	23.972
4	8.417	4.707	6.259	12.833	20.722	25.456	25.702	25.702
5	8.417	4.714	6.290	12.877	20.788	25.886	26.108	26.108
8	8.417	4.713	6.273	12.875	20.858	28.531	29.183	29.183
10	8.417	4.712	6.275	12.884	20.926	28.550	29.060	29.060
15	8.417	4.712	6.275	12.884	20.926	28.550	29.060	29.060

Table 53 RMSE values for increasing number of IMFs with the increase of decomposition levels in LP (VEMD)

IMFs	No. of decomposition levels							
	1	2	3	4	5	8	10	15
1	8.417	6.702	7.640	11.376	18.442	38.432	40.740	41.575
2	8.417	5.409	5.727	10.099	17.593	43.802	46.012	47.588
3	8.417	5.487	5.487	10.808	19.044	43.519	47.064	49.770
4	8.417	5.201	5.314	10.717	30.341	43.175	46.330	48.135
5	8.417	<b>5.199</b>	5.279	10.631	19.473	41.371	43.777	45.729
8	8.417	<b>5.199</b>	5.281	10.635	29.989	40.750	41.967	44.224
10	8.417	<b>5.199</b>	5.281	10.635	29.989	40.750	41.921	42.801
15	NA	NA	NA	NA	NA	NA	NA	NA





#### IV. CONCLUSION

Two types of Empirical Mode Decomposition algorithms viz. BEMD (Bi dimensional Empirical Mode Decomposition) and VEMD (Vectorized Empirical Mode Decomposition) are used to decompose the images to get Intrinsic Mode Functions (IMFs). Performances of these algorithms are evaluated. By performance evaluation metrics, it is concluded that both algorithms are performed similar but VEMD is computationally very simple. Hence VEMD can be adopted for real time applications. Fusion algorithms viz., simple averaging (SA), principal component analysis (PCA), Stationary wavelet transform (SWT) and Laplacian pyramid (LP) are applied on each IMFs to generate the fused IMFs. Fused image is generated by summing all the fused IMFs. Fusion quality evaluation metrics are used to evaluate the fusion algorithms. It is concluded that SWT based image fusion algorithm performs better followed by LP based fusion algorithm. It is also concluded that fusion quality is degraded by using more number of decomposition levels in wavelets and pyramid based image fusion algorithms.

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#### BIOGRAPHY



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